The Journal of Laryngology & Otology

cambridge.org/jlo

# Predicting fall risk in elderly ındividuals: a comparative analysis of machine learning models using patient characteristics, functional balance tests and computerized dynamic posturography

Emre Soylemez[1,2] and Suna Tokgoz-Yilmaz[3,4]

[1]Department of Audiometry, Vocational School of Health Services, Karabuk University, Karabuk, Turkey; [2]Institute of Health Sciences, Audiology and Speech Disorders, Ankara University, Ankara, Turkey; [3]Department of Audiology, Faculty of Health Sciences, Ankara University, Ankara, Turkey and [4]Audiology, Balance and Speech Disorders Unit, Medical Faculty, Ankara University, Ankara, Turkey

## Main Article

Emre Soylemez takes responsibility for the integrity of the content of the paper

**Cite this article:** Soylemez E, Tokgoz-Yilmaz S. Predicting fall risk in elderly ındividuals: a comparative analysis of machine learning models using patient characteristics, functional balance tests and computerized dynamic posturography. *J Laryngol Otol* 2025; **139**:464–472. https://doi.org/10.1017/S0022215124002160

Received: 12 September 2024
Accepted: 14 October 2024
First published online: 11 November 2024

**Keywords:**
balance; elderly ındividuals; fall risk; machine learning; posturography

**Corresponding author:** Emre Soylemez; Email: emresylmz28@gmail.com

## Abstract

**Objectives.** This study aimed to predict the risk of falling using patient characteristics, computerized dynamic posturography and functional balance tests in machine learning.

**Methods.** One hundred twenty elderly individuals were included in this study. The fall status, physical characteristics and medical history of individuals were investigated. Pure tone audiometry test, simple functional balance tests and sensory organization test were applied to the individuals.

**Results.** The machine learning model that incorporated co-morbidities, physical characteristics and functional balance tests achieved a 100 per cent accuracy in predicting fall risk. Models using only co-morbidities and physical characteristics, functional balance tests or the sensory organization test had accuracies of 87.5 per cent, 83.34 per cent and 91.66 per cent, respectively.

**Conclusion.** Advanced balance systems are not always necessary to assess fall risk. Instead, fall risk can be effectively determined using simple balance tests, co-morbidities, and patient characteristics in machine learning.

## Introduction

Aging, which causes biological, physical and functional changes, directly or indirectly causes deterioration in individuals. Approximately one-third of those aged 65 years and over experience a fall once a year. This rate reaches 50 per cent in individuals aged 80 years and over.[1] Falls in elderly individuals can cause superficial injuries or severe injuries, functional disabilities and deaths. Ninety per cent of hip fractures occur as a result of falls, and 25 per cent of elderly individuals who experience hip fractures die shortly after the accident.[2] Even if injuries resulting from falls do not cause severe disabilities, they can cause fear of falling again, self-restraint and anxiety. Thus, it may reduce the quality of life in elderly individuals.

In order to maintain posture and maintain balance, signals from the visual, proprioceptive and vestibular systems must be quickly processed by the central nervous system, and the processed information must be accurately transferred to the musculoskeletal system via efferent pathways. Disruptions in any of these systems can cause imbalance, gait disturbance, dizziness, vertigo and falls in individuals. Whether it is a natural process due to ageing or diseases, deteriorations in balance systems are more common in older individuals.[3] The best method to prevent undesirable consequences of imbalance (falls) is considered to be a multi-component exercise program that includes strength, endurance and balance training.[4] In addition, systematic fall risk assessment is crucial to reduce the prevalence of falls in older individuals.[5] Various tests and scales, both with and without instruments, are generally used in these evaluations. The most well-known of these tests is computerized dynamic posturography (CDP), which evaluates all three balance systems. CDP is very sensitive for determining the risk of falling in elderly individuals, but it is difficult to obtain due to its cost.[6] Functional tests such as the functional reach test (FRT), timed up and go test (TUG), and one-leg stand test (OLST) can be used to assess fall risk without the need for any equipment. However, these tests can give contradictory findings in some cases, and the sensitivity or specificity of some tests is relatively low.[7] Therefore, there is a need for more accurate and more accessible methods to assess fall risk.

Artificial intelligence simulates human behaviour using computers and innovative technologies.[8] Artificial intelligence (machine learning) has recently been used to diagnose

© The Author(s), 2024. Published by Cambridge University Press on behalf of J.L.O. (1984) LIMITED.

diseases and determine disease prognosis.[9] Large data sets regarding diseases or prognoses are provided to the system, and the effect of the data on diagnosis or prognosis is taught to the system. While machine learning algorithms process the inputs, they weigh the effect of the data on the output, which is insufficient to predict the result alone, and a model is created. Models are expected to predict the outcome based on the following inputs provided later with this weighted algorithm. Similarly, machine learning can be used to predict falls due to intrinsic and extrinsic factors. To our knowledge, there is no comprehensive literature study investigating the risk of falls in machine learning using CDP and functional balance tests (FBTs).

This study aims to predict the risk of falling by using patient characteristics, CDP and FBTs in machine learning.

## Material and method

### Ethical situation and participants

This study was conducted on elderly individuals aged 65–79 years. Individuals who underwent neuro-otological examination and were referred to the hearing, balance and speech disorders unit were included in the study. Approval for the study was received from the Ankara University Faculty of Medicine Human Research Ethics Committee (2022000648-2022/648). Verbal and written permission was obtained from all individuals included in the study.

One hundred twenty elderly individuals were included in the study. They were divided into two groups according to their fall status: 65 individuals without a history of falling were included in Group I; 55 elderly individuals who had a history of falling at least once within a year, regardless of any loss of consciousness or an identifiable cause (orthopaedic diseases, stroke, seizure or substance/alcohol use), were included in Group II. Falls were defined as events in which the individual lost balance and came into contact with the ground.

### Criteria for inclusion of individuals in the study

- Age is between 65 and 79 years,
- No history of head trauma,
- Patients do not have complaints/history of vertigo due to diagnosed causes such as Meniere's disease, vestibular neuritis, benign paroxysmal positional vertigo (BPPV),
- Absence of musculoskeletal disorders, vision loss and neurological disease,
- Mini-Mental State Examination (MMSE) score greater than 24.[10]

### Measurements and procedure

Medical history was taken from the participants, and the individual's demographic information, co-morbidities, imbalance and fall conditions were questioned. A patient information form was applied to all individuals, including the medications used. MMSE, audiological evaluation, Romberg test, FRT, OLST, TUG, visual analogue scale (VAS), Tinetti Balance and Gait Test (TBGT) and CDP were applied to all participants.

### Audiological evaluation

A pure tone audiometry test was performed on all individuals included in the study with an AC-40 clinical audiometer (Interacoustics, Denmark) in a quiet cabin. Air conduction hearing thresholds of the participants were determined between 125 and 8000 Hz bilaterally using TDH 39 supra-aural headphones, and bone conduction hearing thresholds were determined between 500 and 4000 Hz bilaterally using radio ear B71 bone vibrator. Pure tone average (PTA) was calculated using the 500, 1000, 2000 and 4000 Hz averages. Hearing was considered normal if PTA was less than 20 dB. PTA between 20 and 40 dB is mild hearing loss, 41–55 dB is moderate hearing loss, 56–70 dB is moderate–severe hearing loss, 71–90 dB is severe hearing loss and gretaer than 90 dB was considered profound hearing loss.[11] A more than 15 dB difference between right and left ear PTAs was considered asymmetric hearing loss.[12] Tympanometric measurements of the elderly individuals included in the study were performed with the GSI Tympstar Version 2 (Grason Stadler, MN, USA) device at 226 Hz probe tone. Participants' bilateral ipsilateral and contralateral acoustic reflex thresholds were determined in the 500–4000 Hz range.

### Evaluation of functional balance

For the Romberg test, participants are asked to take off their shoes, put their feet together, close their eyes and stand in the desired position with their hands at the sides for 30 seconds. The time individuals could stand was recorded with a stopwatch. The test was applied in three different combinations: traditional Romberg, foam pad Romberg and tandem Romberg.[13]

For the OLST, participants were asked to remove their shoes and raise their non-dominant leg. The test was repeated with eyes open and closed. Individuals were expected to stand in the desired position (eyes open/closed) for 30 seconds without losing balance. The time to stay in balance was recorded with a stopwatch.[14]

For FRT, participants were asked to stand with their feet shoulder-width apart and stand parallel to the wall where a tape measure was placed, not touching the wall. Individuals were asked to flex their shoulders on the side of the tape measure to 90 degrees and make a fist with their hands. The individual's third interphalanx joint level was marked on the tape measure, and they were asked to lie forward as far as they could without moving their feet. The maximum distance the individual could reach was marked again on the tape measure. The difference between the first distance and the second distance was calculated.[15]

For TUG, participants were asked to sit on a chair with a height of approximately 50 cm, stand up with the "start" command, walk the 3-meter walking track quickly, return from the endpoint and quickly sit on the chair again. The individuals' time to complete the course was measured with a stopwatch.[16]

TBGT was developed by Mary Tinnetti and consists of two parts.[17] The first part consists of 13 items and includes balance; the second part consists of 9 items and evaluates walking. The total score is calculated out of 35.

### VAS

The participants' imbalance severity was evaluated with VAS. The endpoints of a 10 cm line drawn on paper were numbered 0 (no imbalance) and 10 (extreme imbalance). Individuals were asked to mark a point on this line appropriate to their imbalance's severity.[18]

### CDP

CDP testing was performed with Smart Equitest Dynamic Posturography (NeuroCom Balance Manager Systems, Natus Medical, USA). Participants were asked to wear safety vests to prevent falls, and the sensory organization test (SOT) was applied to the individuals taken to the platform. SOT, each condition

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press

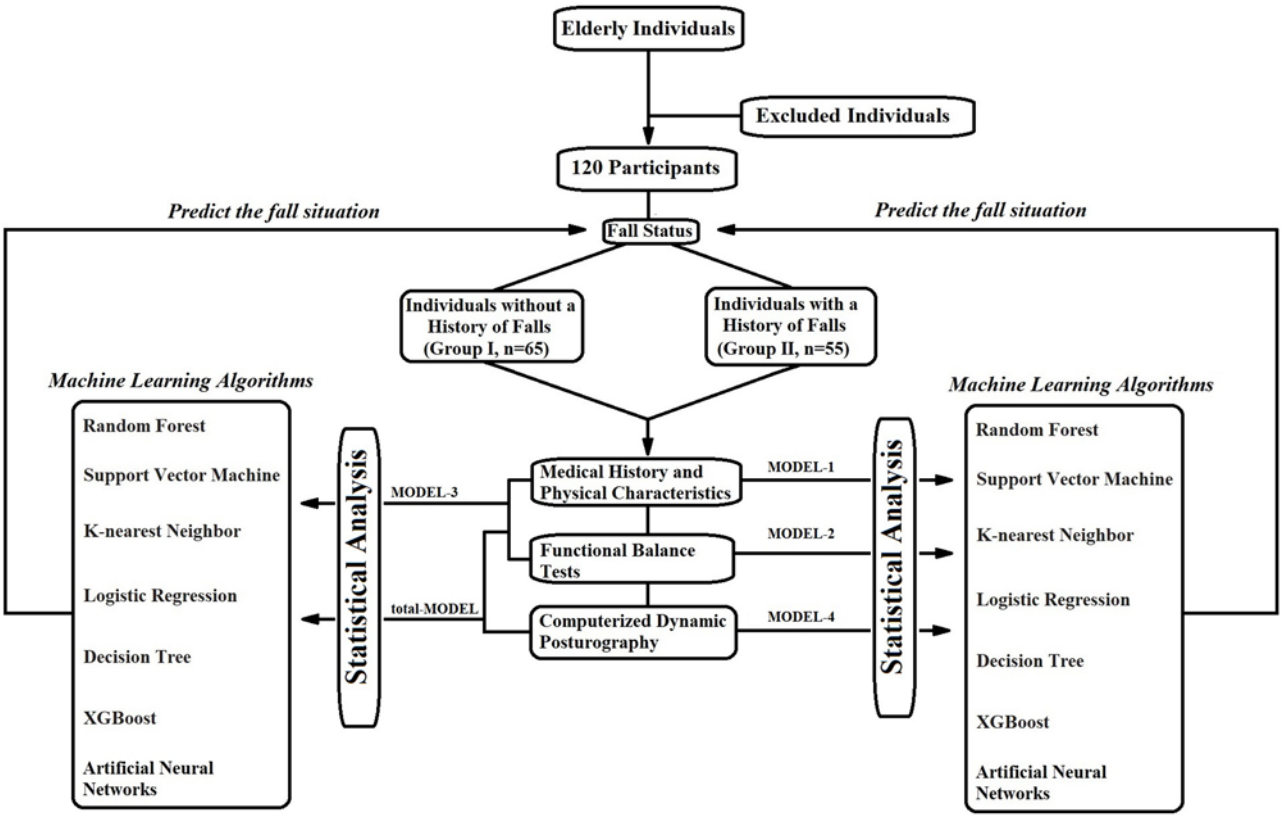



**Figure 1.** The flow chart of the procedures and models applied to the participants.

lasting 20 seconds; It evaluates six different situations, and three consecutive repetitions are made for each situation.[19]

SOT 1: Eyes open, platform and surface stable.
SOT 2: Eyes closed, platform and surface stable.
SOT 3: Eyes open, platform moving and surface stationary.
SOT 4: Eyes open, platform stationary and surface moving.
SOT 5: Eyes closed, platform stationary and surface moving.
SOT 6: Eyes open, platform and surface moving.

## Machine learning and feature selection

Python (Version 3.7) programming language was used for machine learning. Our study used supervised learning algorithms k-nearest neighbors (KNN), naive Bayes, decision trees, random forest, support vector machine (SVM), logistic regression, XGBoost and artificial neural networks (ANN). While modelling the algorithms, 96 (80 per cent) of the data were used in the training process, and the remaining 24 (20 per cent) were used in the testing process. Individuals' ages, demographic information, co-morbidities, and balance tests were defined as input attributes. The patients' fall status was defined as output. A hyperparameter selection Grid Search method was used. A statistical analysis method was used to determine the study's input features. In statistical analysis, data with a significance level of $p < 0.05$ were defined as attributes (variables with no significant difference between groups were not used in machine learning). Statistical analysis was performed with IBM SPSS 21. Student's $t$-test is used to compare groups when normality assumptions are met. In cases where the assumptions were not met, the Mann–Whitney U test was used. The performances of the algorithms were evaluated with their success rates in the testing phase. The area under the receiver operating characteristics curve (AUC-ROC) was considered if the success rate was equal between the algorithms. In our study, five different models were created using five different feature groups. These models were MODEL-1 (anamnesis, diseases and physical characteristics data), MODEL-2 (FBTs data), MODEL-3 (MODEL-1 and MODEL-2), MODEL-4 (SOT data) and total-MODEL (all features). The flow chart of the procedures and models applied to the participants is presented in Figure 1.

## Results

Of the individuals in Group I, 33 were female, 32 were male, and the average age was 69.13±4.58 years. Of the individuals in Group II, 37 were female, 18 were male, and the average age was 70.20±4.70 years. There was no difference between the groups in terms of age and gender ($p = 0.175$, 0.068, respectively).

Individuals in Group II were shorter in height and had a higher body mass index (BMI) than those in Group I ($p < 0.05$). Additionally, complaints of imbalance, severity of hearing loss, and the prevalence of diabetes mellitus and hypertension were higher in Group II than in Group I ($p < 0.05$). Additionally, the severity and duration of imbalance in individuals in Group II were greater than in individuals in Group I ($p < 0.001$). Eyes open and closed OLST, foam pad Romberg test, tandem Romberg test, FRT, TUG and all SOT scores of individuals in Group II were worse than those in Group I ($p < 0.001$). The physical characteristics, co-morbidities, FBTs and SOT scores of the participants according to the groups are presented in Table 1. According to SOT, the somatosensory, visual, vestibular and composite scores of individuals in Group II were

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press

**Table 1.** Physical characteristics, co-morbidities, functional balance tests and sensory organization test scores of the participants according to groups

| | Group I, n = 65 Mean±SD or median (min-max) | Group II, n = 55 Mean±SD or median (min-max) | *p*-Value |
|---|---|---|---|
| *Physical properties* | | | |
| Weight, kg | 73.81±11.67 | 72.23±12.51 | 0.476[d] |
| Height, cm | 165.29±8.73 | 156 (143–182) | <**0.001**[a] |
| Body mass index (BMI) | 27.10±4.50 | 29.04±4.97 | **0.027**[d] |
| *Co-morbidities and medication* | | | |
| No. of medications | 0 (0–5) | 1 (0–10) | 0.144[a] |
| Imbalance symptom, n (%) | 15 (%23.1) | 44 (%80.0) | <**0.001**[b] |
| Imbalance severity | 0 (0–5) | 4 (0–8) | <**0.001**[a] |
| Duration of imbalance (months) | 0 (0–36) | 10 (0–120) | <**0.001**[a] |
| *Diseases, n (%)* | | | |
| Hypertension, n (%) | 25 (%38.5) | 32 (%58.2) | **0.031**[b] |
| Diabetes mellitus, n (%) | 10 (%15.4) | 18 (%32.7) | **0.025**[b] |
| Hyperlipidemia, n (%) | 11 (%16.9) | 12 (%21.8) | 0.497[b] |
| Cardiovascular diseases, n (%) | 8 (%12.3) | 5 (%9.1) | 0.572[b] |
| Thyroid, n (%) | 2 (%3.1) | 2 (%3.6) | 0.625[c] |
| Major depression disorder, n (%) | 2 (%3.1) | 1 (%1.8) | 0.660[c] |
| Prostate, n (%) | 1 (%1.5) | 1 (%1.8) | 0.709[c] |
| Right Ear PTA (dB) | 40 (12.5–75) | 57.48±24.60 | <0.001[a] |
| Left Ear PTA (dB) | 41.25 (8.75–98.75) | 53.85±22.61 | <0.001[a] |
| No. of individuals with hearing loss n, (%) | 51 (%78.5) | 50 (%90.9) | <0.001[b] |
| Mild | 35 (%53.8) | 13 (%23.6) | |
| Moderate | 18 (%27.6) | 12 (%21.8) | |
| Moderately severe | 3 (%4.6) | 19 (%34.5) | |
| Severe | 0 (%0) | 5 (%9.1) | |
| Profound | 0 (%0) | 1 (%1.8) | |
| Asymmetric hearing hoss (n) | 14 (%21.5) | 18 (%32.7) | 0.167[b] |
| *Functional balance tests* | | | |
| Romberg test (sec) | 30.00 (25.67–30.00) | 30.00 (15.05–30.00) | 0.287[a] |
| Foam padRomberg (sec) | 30.00 (5.42–30.00) | 11 (1.63–30.00) | <0.001[a] |
| Tandem Romberg test (sec) | 13.54 (2.37–30.00) | 5.67 (1.11–30.00) | <0.001[a] |
| *One leg standing test (sec)* | | | |
| Open eyes | 16.82 (4.21–30.00) | 4.85 (1.52–30) | <0.001[a] |
| Closed eyes | 5.74 (1.34–30.00) | 2.76 (0.30–16.15) | <0.001[a] |
| Timed up and Go (sec) | 8.34±1.36 | 10.08 (7.27–17.56) | <0.001[a] |
| Functional reach test (cm) | 29.32±5.08 | 22.71±5.32 | <0.001[d] |
| Tinetti balance and gait test | 35 (33–35) | 33 (27–35) | <0.001[a] |
| *Sensory organization test* | | | |
| SOT1 | 94.00 (88.34–96.67) | 91.33 (60.66–97.00) | <0.001 |
| SOT2 | 93.67 (85.67–96.67) | 89.34 (58.00–96.67) | <0.001 |
| SOT3 | 92.00 (81.34–97.34) | 87.00 (0.00–95.67) | <0.001 |
| SOT4 | 79.07±7.45 | 68.00 (0.00–97.00) | <0.001 |
| SOT5 | 68.67 (39.34–86.34) | 44.36±24.04 | <0.001 |
| SOT6 | 66.03±10.94 | 43.00 (0.00–93.00) | <0.001 |

worse than those in Group I ($p < 0.05$). However, there was no difference between the groups in terms of visual preference ($p > 0.05$). Somatosensory, visual, vestibular, composite and visual preference scores according to groups are presented in Figure 2.

In MODEL-1, created using medical history and physical features, KNN, naive Bayes, random forest, XGBoost and ANN reached the highest accuracy rate with 87.5 per cent. The naive Bayes algorithm had the highest AUC-ROC value of 0.979 among the five algorithms. In MODEL-2, created using FBTs, naive Bayes, KNN, SVM, ANN and logistic regression reached the highest accuracy rate of 83.5 per cent. The logistic regression algorithm had the highest AUC-ROC value of 0.944 among the four algorithms. The SVM algorithm reached the highest accuracy rate with 100 per cent in MODEL-3, created using the features used to develop MODEL-1 and MODEL-2 together. In MODEL-4, created using SOT values, XGBoost reached the highest accuracy rate with 91.6 per cent. In the total-MODEL created using all attributes, naive Bayes reached the highest accuracy rate with 100 per cent. The test successes of the models are presented in Table 2. Confusion matrices and ROC curves of the best-performing algorithms according to the models are presented in Figure 3.

## Discussion

This study aimed to predict the risk of falling using patient characteristics, CDP, and FBTs in machine learning. For this purpose, we created five different machine-learning models using different parameters. The model built using SOT data predicted fall risk with 91.6 per cent accuracy (XGBoost/MODEL-4). The model

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press

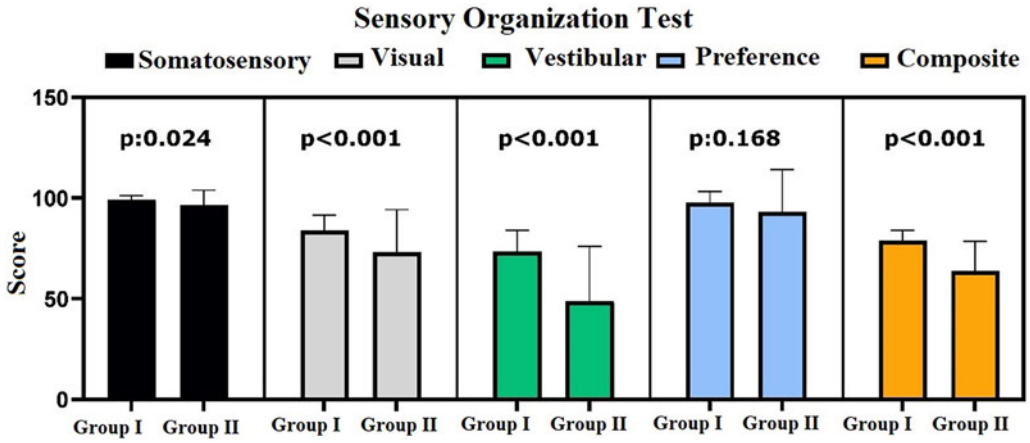



**Figure 2.** Somatosensory, visual, vestibular, composite and visual preference scores according to groups.

**Table 2.** Test success of the models

| Algorithms | Precision | Recall | F1-score | Accuracy | AUC-ROC |
|---|---|---|---|---|---|
| **MODEL−1** | | | | | |
| KNN | 0.90 | 0.82 | 0.86 | 0.8750 | 0.933 |
| **Naive Bayes** | **0.83** | **0.91** | **0.87** | **0.8750** | **0.979** |
| Decision tree | 0.73 | 0.73 | 0.73 | 0.7550 | 0.748 |
| Random forest | 0.91 | 0.91 | 0.91 | 0.8750 | 0.951 |
| SVM | 0.82 | 0.82 | 0.82 | 0.8334 | 0.972 |
| Logistic regression | 0.82 | 0.82 | 0.82 | 0.8334 | 0.972 |
| XGBoost | 0.90 | 0.82 | 0.86 | 0.8750 | 0.937 |
| Artificial neural networks | 0.82 | 0.82 | 0.82 | 0.8334 | 0.832 |
| **MODEL−2** | | | | | |
| KNN | 0.82 | 0.82 | 0.82 | 0.8334 | 0.898 |
| Naive Bayes | 0.77 | 0.91 | 0.83 | 0.8334 | 0.937 |
| Decision tree | 0.78 | 0.64 | 0.70 | 0.7500 | 0.842 |
| Random forest | 0.75 | 0.82 | 0.78 | 0.7916 | 0.951 |
| SVM | 0.82 | 0.82 | 0.82 | 0.8334 | 0.930 |
| **Logistic Regression** | **0.82** | **0.82** | **0.82** | **0.8334** | **0.944** |
| XGBoost | 0.82 | 0.82 | 0.82 | 0.8334 | 0.881 |
| Artificial neural networks | 0.80 | 0.73 | 0.76 | 0.7916 | 0.786 |
| **MODEL−3** | | | | | |
| KNN | 1.00 | 0.82 | 0.90 | 0.9166 | 0.979 |
| Naive Bayes | 0.85 | 1.00 | 0.92 | 0.9166 | 0.986 |
| Decision tree | 0.82 | 0.82 | 0.82 | 0.8334 | 0.832 |
| Random forest | 0.91 | 0.91 | 0.91 | 0.9166 | 0.972 |
| **SVM** | **1.00** | **1.00** | **1.00** | **1.0000** | **1.000** |
| Logistic regression | 0.77 | 0.91 | 0.83 | 0.8334 | 0.965 |
| XGBoost | 0.91 | 0.91 | 0.91 | 0.9166 | 0.940 |
| Artificial neural networks | 0.85 | 1.00 | 0.92 | 0.9166 | 0.923 |

(*Continued*)

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press

**Table 2.** (*Continued.*)

| Algorithms | Precision | Recall | F1-score | Accuracy | AUC-ROC |
|---|---|---|---|---|---|
| **MODEL−4** | | | | | |
| KNN | 0.89 | 0.73 | 0.80 | 0.8334 | 0.825 |
| Naive Bayes | 1.00 | 0.73 | 0.84 | 0.8750 | 0.930 |
| Decision tree | 0.89 | 0.73 | 0.80 | 0.8334 | 0.814 |
| Random forest | 0.89 | 0.73 | 0.80 | 0.8334 | 0.888 |
| SVM | 0.88 | 0.64 | 0.74 | 0.7916 | 0.867 |
| Logistic regression | 0.88 | 0.64 | 0.74 | 0.7916 | 0.867 |
| **XGBoost** | **1.00** | **0.82** | **0.90** | **0.9166** | **0.895** |
| Artificial neural networks | 0.90 | 0.82 | 0.86 | 0.8750 | 0.871 |
| **MODEL−5** | | | | | |
| KNN | 1.00 | 0.82 | 0.90 | 0.9166 | 0.909 |
| **Naive Bayes** | **1.00** | **1.00** | **1.00** | **1.0000** | **1.000** |
| Decision tree | 1.00 | 0.91 | 0.95 | 0.9583 | 0.975 |
| Random forest | 0.90 | 0.82 | 0.86 | 0.8750 | 0.972 |
| SVM | 0.89 | 0.73 | 0.80 | 0.8334 | 0.937 |
| Logistic regression | 0.78 | 0.64 | 0.70 | 0.7500 | 0.881 |
| XGBoost | 0.91 | 0.91 | 0.91 | 0.9166 | 0.993 |
| Artificial neural networks | 1.00 | 0.73 | 0.84 | 0.8750 | 0.863 |

Bold text: algorithm with best success, KNN: K-nearest neighbor, SVM: support vector machine, AUC-ROC: area under the receiver operating characteristic curve.

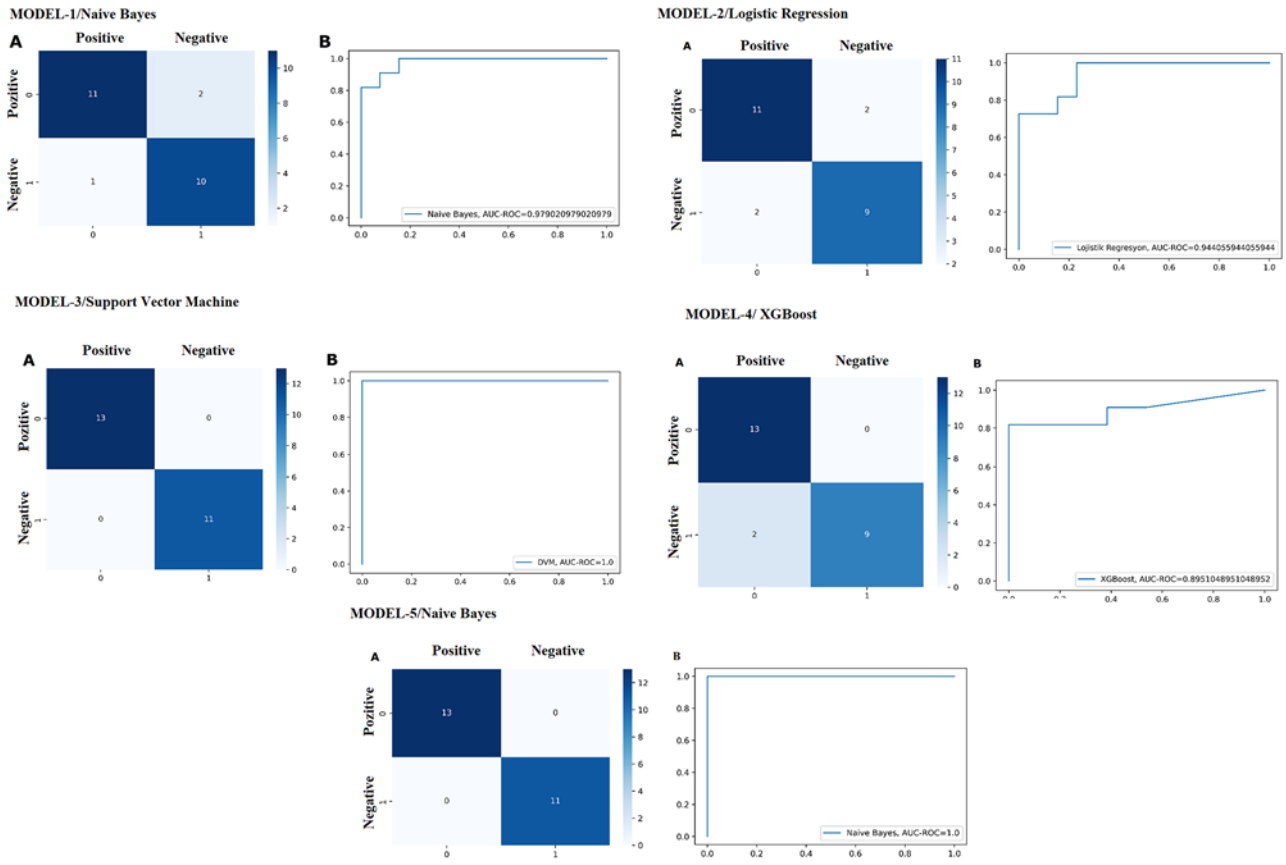



**Figure 3.** Confusion matrices and ROC curves of the best-performing algorithms according to the models.

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press

created using individuals' co-morbidities and physical characteristics predicted the risk of falling with 87.5 per cent accuracy (naive Bayes /MODEL-1). The model created using individuals' functional balance scores predicted the risk of falling with 83.3 per cent accuracy (Logistic regression/MODEL-2). The model created using individuals' diseases, physical characteristics and functional balance scores predicted the risk of falling with 100 per cent accuracy (SVM/MODEL-3).

It is known that the risk and prevalence of falls increase with ageing. Deterioration in the visual system, hearing loss, cognitive decline and decreased muscle tone and reflexes caused by ageing increase the risk of falling. Approximately 30 per cent of individuals over the age of 65 years fall each year, and approximately half of these individuals experience relapses.[20] We included individuals aged 65–79 years in our study and did not detect any difference in age between elderly individuals who fell and those who did not fall. This finding shows that the risk of falling does not change significantly between the ages of 65 and 79 years.

It is known that women fall more than men and that women suffer from more fractures due to falls. Although the reason for this difference is not fully understood, various opinions have been put forward.[21,22] Bone mineral density decreases in women due to menopause. Reduced bone mineral density may cause women to fall more frequently and cause more fractures due to falls.[21] Similarly, our study found that women fell more than men (67.3 per cent vs. 50.4 per cent), but this difference was not statistically significant.

Obesity and its complications cause many diseases and affect the daily lives of individuals. Moreover, obesity may increase the risk of falling in older individuals. Mijangos *et al.*[23] reported that gait and balance deteriorate and falls increase as BMI increases. Similarly, in our study, the BMI of older people who fell was higher than that of those who did not. Increasing BMI can affect individuals' musculoskeletal systems and change the body's centre of gravity (geometry). Additionally, Son[24] reported that the feet of obese individuals are exposed to too much force, and accordingly, the proprioceptive inputs in the feet become desensitized (plantar desensitization). However, in our study, there was no difference in weight between individuals who fell and those who did not. The difference in BMI between the groups was due to height, meaning that shorter ones had a higher risk of falling. Therefore, plantar desensitization cannot explain the observed falls in individuals with high BMI in our study. In our study, the possible reason for the higher risk of falling in individuals with high BMI was interpreted as changes in body geometry and gait.

Risk factors for falls in older individuals are complex. In addition to known risk factors such as vertigo, musculoskeletal disorders and visual disorders, medications used or diseases that seem unrelated to falls can also cause falls. A combination of these risk factors often causes an individual's fall. Some diseases, such as arthritis, diabetes mellitus, hypertension and chronic obstructive pulmonary disease, may increase the risk of falls in older individuals.[25] In the literature, it has been stated that the use of certain medicines (opioids, benzodiazepines, diuretics, vasodilators, etc.) and the use of more than five (number of) medicines cause gait and balance disorders and increase the rate of repeated falls.[26] Similar to the literature, our study determined that imbalance symptoms, hypertension, diabetes mellitus and hearing loss were risk factors for falls. However, there was no difference between the groups in terms of the total number of medications used, hyperlipidemia, depression, cardiovascular diseases, thyroid and prostate. The fact that the number of medicines used in our study did not pose a risk of falling can be explained by our criteria for including individuals in the study. Our study included those who fell at least once in the past year. It is known that the total number of medicines used causes repeated falls, not single falls.[26]

Studies on machine learning and falls in the literature generally focus on detecting falls (video cameras, etc.).[27] In machine learning studies aiming to predict the risk of falling, electronic health records, surveys, scales, hospital admission evaluations, TUG and sit-to-stand tests were generally used.[28] In a retrospective study by Thapa *et al.*[29] using electronic health records, data from 2785 individuals were used. The fall risk of these individuals was estimated using machine learning with 68 attributes such as age, gender, diseases, and medications used. The study reported that Extreme Gradient Boosting predicted the risk of falling with 84.8 per cent sensitivity and 70.6 per cent specificity. However, it was reported that incomplete and unevenly distributed data limited the study. Ikeda *et al.*[30] predicted fall risk with XGBoost and random forest algorithms using 14 attributes such as depressive symptoms, age, health status and urinary incontinence. The authors reported that the XGBoost algorithm predicted falls with 88 per cent accuracy. Fahimi *et al.*[31] applied three functional tests (force production, postural sway and gait evaluation) to 80 elderly individuals and created machine learning models using the data of these tests. The authors reached the highest accuracy rate of 74.50 per cent with the KNN algorithm. Ziegl *et al.*[32] used TUG data of elderly individuals living in nursing homes in the random forest algorithm and stated that the model could predict falls with an AUC-ROC rate of 96.9 per cent. In another study, Tongterm *et al.*[33] used functional fitness tests in machine learning and aimed to predict the risk of falling with the decision tree. The authors determined the model's accuracy to be 0.95 and the specificity to be 0.55. To the best of our knowledge, no study in the literature detects fall risk using SOT data in machine learning. Unlike other studies, we used the features individually (SOT, FBT and medical/physical features) and in combination when creating machine learning models. XGBoost, one of the algorithms created with SOT, considered the gold standard test for evaluating balance, predicted the risk of falling with 91.6 per cent accuracy (MODEL-4). SVM, one of the algorithms created using individuals' co-morbidities, physical characteristics and simple FBTs, predicted the risk of falling with 100 per cent accuracy (MODEL-3). Similarly, naive Bayes, one of the algorithms in which all features (23 features) were used in machine learning (total-MODEL), predicted the risk of falling with 100 per cent accuracy.

Falls in elderly individuals occur due to physical, perceptual and cognitive changes combined with diseases and an environment unsuitable for the safety of the elderly. Our study found that SOT administered with CDP is the most reliable test that can be used alone to predict fall risk. CDP is objective and evaluates all balance parameters. However, in addition to being a complex and expensive test, it also takes time. Moreover, our study found that the machine learning model (MODEL-3) created with simple FBTs and co-morbidities/physical characteristics detected the risk of falling at a higher rate than CDP. This shows that, although balance tests used to assess fall risk are reliable, individuals' diseases and physical characteristics should also be taken into account. By using FBTs, individuals' co-morbidities and physical characteristics in machine learning, the fall risk of elderly individuals can be predicted quickly and cheaply. This way, individuals at risk of falling can be identified early, and fall prevention strategies (exercise, awareness raising and ergonomics) can be recommended.

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press

There are several limitations to this study. First, the sample size included in the study is limited to 120 elderly individuals. The prospective nature of the research and the long duration of the tests limited the sample size. In future studies, larger sample groups can be examined with retrospective data. In addition, despite the success of MODEL-3 and its potential to be applied without requiring a special device, this study was tested on a limited sample. Studies with larger sample groups will allow a better assessment of the general applicability and effectiveness of MODEL-3. Thus, an essential first step may have been taken in developing applicable methods to determine the global fall risk in elderly individuals.

- Fall risk can be assessed using a range of both simple balance tests and advanced balance platforms
- Balance test results can sometimes be contradictory, making it challenging to determine which results to trust
- Also, falls are multidimensional and can result from various factors, including sensory disorders, inattention, diseases, and medications
- Therefore, simpler methods are needed to estimate fall risk by evaluating multiple factors and providing a single result (there is a risk of falling or not)
- In this study, machine learning was used to develop models that predict fall risk with high accuracy, based on individuals' co-morbidities, balance tests and physical characteristics

## Conclusion

Although balance tests to assess fall risk are reliable, individuals' diseases and physical characteristics should also be considered. Fall risk can be successfully predicted using simple FBTs, co-morbidities and individuals' physical characteristics in the SVM algorithm. Moreover, machine learning-based websites or mobile applications can be developed with these models. In this way, elderly individuals can detect the risk of falling with online counselling without resorting to clinics. Similarly, online fall prevention strategies can be recommended to these individuals.

**Acknowledgment.** We acknowledge the volunteers for their contribution to this study.

**Author contributions.** This research was conducted as the doctoral thesis of Emre Söylemez at Ankara University Health Sciences Institute. Emre Soylemez (ORCID ID: 0000-0002-7554-3048): Data collection, statistical analysis and data interpretation, writing the article. Suna Tokgoz-Yilmaz (ORCID ID: 0000-0002-4656-099X): Finding the topic, methodology, final revision, writing the article

**Funding statement.** The authors report that there was no funding source for the work that resulted in the article or the preparation of the article.

**Competing interests.** The authors declare no conflicts of interest.

**Ethical standards.** An approval was received from local ethics committee Ankara University Faculty of Medicine Human Research Ethics Committee (2022000648-2022/648). Written approval was received from all subjects involved in the study.

## References

1 Burt CW, Fingerhut LA. Injury visits to hospital emergency departments: United States, 1992-95. *Vital Health Stat* 1998;**131**:1–76
2 Black SE, Maki BE, Fernie GR. Aging, imbalance and falls. In: Barber H, Sharp HO, eds. *The Vestibulo-ocular Reflex and Vertigo*. Seattle: Raven Press, 1993;317–35
3 Kerber KA, Enrietto JA, Jacobson KM Baloh RW. Disequilibrium in older people: a prospective study. *Neurology* 1998;**51**:574–80
4 Cadore EL, Rodríguez-Mañas L, Sinclair A. Izquierdo M. Effects of different exercise interventions on risk of falls, gait ability, and balance in physically frail older adults: a systematic review. *Rejuvenation Res* 2013;**16**:105–14
5 Rubenstein LZ. Falls in older people: epidemiology, risk factors and strategies for prevention. *Age Ageing* 2006;**35**:ii37–41
6 Müjdeci B, Aksoy S, Atas A. Evaluation of balance in fallers and non-fallers elderly. *Braz J Otorhinolaryngol* 2012;**78**:104–9
7 Kozinc Ž, Löfler S, Hofer C, Carraro U, Šarabon N. Diagnostic balance tests for assessing risk of falls and distinguishing older adult fallers and non-fallers: a systematic review with meta-analysis. *Diagnostics (Basel)* 2020;**10**:667
8 Amisha Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. *J Family Med Prim Care* 2019;**8**:2328–31
9 Abbasgholizadeh Rahimi S, Légaré F, Sharma G, Archambault P, Zomahoun HTV, Chandavong S, *et al.* Application of artificial ıntelligence in community-based primary health care: systematic scoping review and critical appraisal. *J Med Internet Res* 2021;**23**:e29839
10 Güngen C, Ertan T, Eker E, Yaşar R, Engin F. [Reliability and validity of the standardized Mini Mental State Examination in the diagnosis of mild dementia in Turkish population]. *Turk Psikiyatri Derg* 2002;**13**:273–81
11 Ajmani S, Keshri A, Srivastava R, Aggarwal A, Lawrence A. Hearing loss in ankylosing spondylitis. *Int J Rheum Dis* 2019;**22**:1202–8
12 Noh H, Lee D-H. Predictable factors of people with asymmetrical hearing loss wearing a hearing aid in the worse ear only. *J Clin Med* 2023;**14**;12:2251
13 Forbes J, Munakomi S, Cronovich HA. Romberg Test. In StatPearls. *StatPearls Publishing Copyright* 2023. https://www.ncbi.nlm.nih.gov/books/NBK563187/ [19 March 2025]
14 Vellas BJ, Wayne SJ, Romero L, Baumgartner RN, Rubenstein LZ, Garry PJ. One-leg balance is an important predictor of injurious falls in older persons. *J Am Geriatr Soc* 1997;**45**:735–8
15 Duncan PW, Weiner DK, Chandler J, Studenski S. Functional reach: a new clinical measure of balance. *J Gerontol* 1990;**45**:M192–7
16 Podsiadlo D, Richardson S. The timed "Up & Go": a test of basic functional mobility for frail elderly persons. *J Am Geriatr Soc* 1991;**39**:142–8
17 Tinetti ME. Performance-oriented assessment of mobility problems in elderly patients. *J Am Geriatr Soc* 1986;**34**:119–26
18 Wewers ME, Lowe NK. A critical review of visual analogue scales in the measurement of clinical phenomena. *Res Nurs Health* 1990;**13**:227–36
19 Vanicek N, King SA, Gohil R, Chetter IC, Coughlin PA. Computerized dynamic posturography for postural control assessment in patients with intermittent claudication. *J Vis Exp* 2013:e51077
20 Akyol AD. Falls in the elderly: what can be done? *Int Nurs Rev* 2007;**54**:191–6
21 Gale CR, Cooper C, Aihie Sayer A. Prevalence and risk factors for falls in older men and women: The English Longitudinal Study of Ageing. *Age Ageing* 2016;**45**:789–94
22 Johansson J, Nordström A, Nordström P. Greater fall risk in elderly women than in men is associated with increased gait variability during multitasking. *J Am Med Dir Assoc* 2016;**17**:535–40
23 Mijangos ADS, la Cruz PG, Alfaro LIS, Ribón TS. Factores de riesgo de caídas e índice de masa corporal en el adulto mayor hospitalizado. *Rev Cuid* 2019;**10**:e621
24 Son SM. Influence of obesity on postural stability in young adults. *Osong Public Health Res Perspect* 2016;**7**:378–81
25 Sibley KM, Voth J, Munce SE, Straus SE, Jaglal SB. Chronic disease and falls in community-dwelling Canadians over 65 years old: a population-based study exploring associations with number and pattern of chronic conditions. *BMC Geriatr* 2014;**14**:22
26 Morris M, Osborne D, Hill K, Kendig H, Lundgren-Lindquist B, Browning C, *et al.* Predisposing factors for occasional and multiple

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press

falls in older Australians who live at home. *Aust J Physiother* 2004;**50**: 153–9
27 Usmani S, Saboor A, Haris M, Khan MA, Park H. Latest research trends in fall detection and prevention using machine learning: a systematic review. *Sensors (Basel)* 2021;**21**:5134
28 Yadav P, Vijay V. Fall prediction using machine learning - a systematic review. *Am J Biomed Sci Res* 2023;**18**:637–46
29 Thapa R, Garikipati A, Shokouhi S, Hurtado M, Barnes G, Hoffman J, *et al*. Predicting falls in long-term care facilities: machine learning study. *JMIR Aging* 2022;**5**:e35373
30 Ikeda T, Cooray U, Hariyama M, Aida J, Kondo K, Murakami M, *et al*. An interpretable machine learning approach to predict fall risk among community-dwelling older adults: a three-year longitudinal study. *J Gen Intern Med* 2022;**37**:2727–35
31 Fahimi F, Taylor WR, Dietzel R, Armbrecht G, Singh Nb. Identifying fallers based on functional parameters: a machine learning approach. 2021 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE) 2021;1–6
32 Ziegl A, Hayn D, Kastner P, Loffler K, Weidinger L, Brix B, et al. Machine learning based walking aid detection in timed up-and-go test recordings of elderly patients. Annu Int Conf IEEE Eng Med Biol Soc 2020; 808–11
33 Tongterm T, Suputtitada A, Lawsirirat C, Janwantanakul P. Functional fitness test for screening the risk of falls in the elderly: using decision tree technique. J Exer Physiol Online 2015;**18**:104

https://doi.org/10.1017/S0022215124002160 Published online by Cambridge University Press